

Scalability Issues in Sparse Factorization and Triangular Solution

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Overview

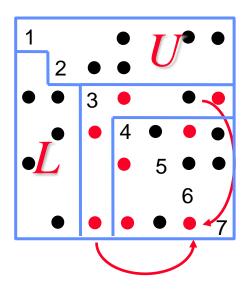


- Basic algorithms
- Partitioning, processor assignment at different phases
- Scalability issues
- Current & future work

Sparse GE



- Scalar algorithm: 3 nested loops
 - Can re-arrange loops to get different variants: left-looking, right-looking, . . .



```
for i = 1 to n
  column_scale ( A(:,i) )
  for k = i+1 to n s.t. A(i,k) != 0
    for j = i+1 to n s.t. A(j,i) != 0
    A(j,k) = A(j,k) - A(j,i) * A(i,k)
```

- > Typical fill-ratio: 10x for 2D problems, 30-50x for 3D problems
- Finding fill-ins is equivalent to finding transitive closure of G(A)

Major stages



- 1. Order equations & variables to preserve sparsity
 - NP-hard, use heuristics
- 2. Symbolic factorization
 - Identify supernodes, set up data structures and allocate memory for L & U.
- 3. Numerical factorization usually dominates total time
 - How to pivot?
- 4. Triangular solutions usually less than 5% total time

SuperLU_MT

- 1. Sparsity ordering
- 2. Factorization
 - Partial pivoting
 - Symbolic fact.
 - Num. fact. (BLAS 2.5)
- 3. Solve

SuperLU_DIST

- 1. Static pivoting
- 2. Sparsity ordering
- 3. Symbolic fact.
- 4. Numerical fact. (BLAS 3)
- 5. Solve

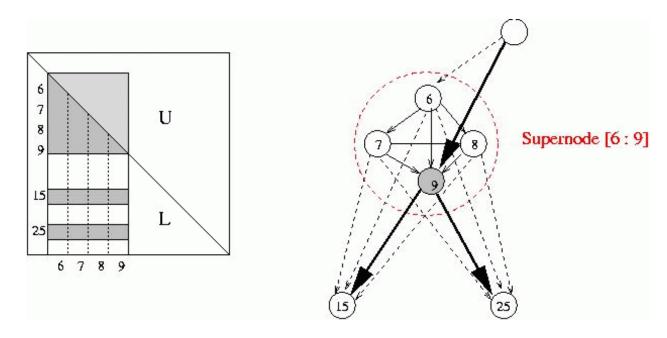
SuperLU_DIST steps:



- Static numerical pivoting: improve diagonal dominance
 - Currently use MC64 (HSL, serial)
 - Being parallelized [J. Riedy]: auction algorithm
- Ordering to preserve sparsity
 - Can use parallel graph partitioning: ParMetis, Scotch
- Symbolic factorization: determine pattern of {L\U}
 - Parallelized [L. Grigori et al.]
 - Numerics: Parallelized
 - Factorization: usually dominate total time
 - Triangular solutions
 - Iterative refinement: triangular solution + SPMV

Supernode: dense blocks in {L\U}





- Good for high performance
 - Enable use of BLAS 3
 - Reduce inefficient indirect addressing (scatter/gather)
 - Reduce time of the graph algorithms by traversing a coarser graph

Matrix partitioning at different stages

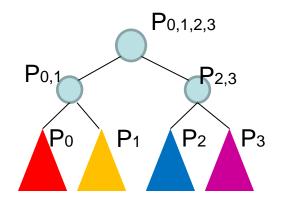


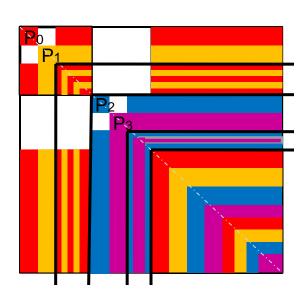
- Distributed input A (user interface)
 - 1-D block partition (distributed CRS format)
- Parallel symbolic factorization
 - Tied with a ND ordering
 - Distribution using separator tree, 1-D within separators
- Numeric phases
 - 2-D block cyclic distribution

Parallel symbolic factorization



- Tree-based partitioning / assignment
- Use graph partitioning to reorder/partition matrix
 - ParMetis on graph of A + A'
- `Arrow-head', two-level partitioning
 - separator tree: subtree-tosubprocessor mapping
 - within separators: 1-D block cyclic distribution
- Disadvantage: works only with ND ordering, and a binary tree





Memory result of parallel symbolic

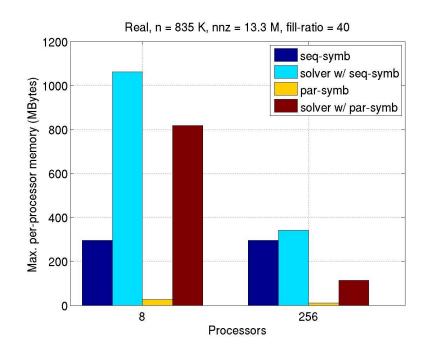


Maximum per-processor memory

Fusion: matrix181 (*M3D-C1*)

Real, n = 590 K, nnz = 94.9 M, fill-ratio = 9 Seq-symb Solver w/ seq-symb Par-symb Solver w/ par-symb Solver w/ par-symb Par-symb Solver w/ par-symb

Accelerator: dds15 (Omega3P)



Runtime of parallel symbolic, IBM Power5



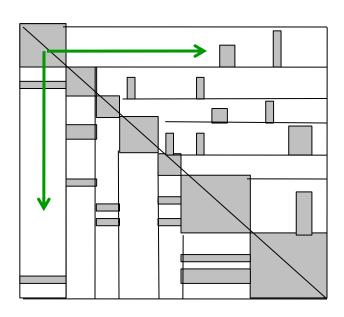
matrix181		P = 8	P = 256
symbolic	Sequntial	6.8	6.8
	Parallel	2.6	2.7
Entire solver	Old	84.7	26.6
	New	159.2	26.5

dds15		P = 8	P = 256
symbolic	Sequntial	4.6	4.6
	Parallel	1.6	0.5
Entire solver	Old	64.1	43.2
	New	66.3	31.4

Numeric phases: 2-D partition by supernodes



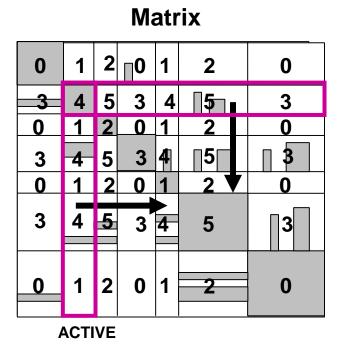
- Find supernode boundaries from columns of L
 - Not to exceed MAXSUPER (~50)
- Apply same partition to rows of U
- Diagonal blocks are square, full, <= MAXSUPER;
 off-diagonal blocks are rectangular, not full

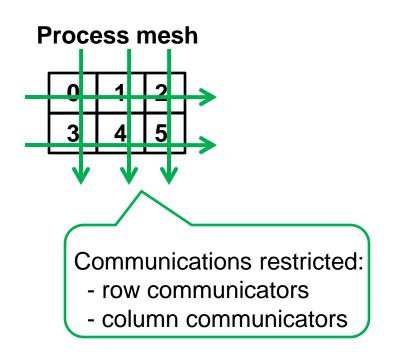


Processor assignment in 2-D



- 2D block cyclic layout
- One step look-ahead to overlap comm. & comp.
- Scales to 1000s processors



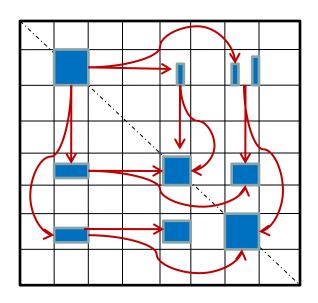


➤ Disadvantage: inflexible

Block dependency graph – DAG



- Based on nonzero structure of L+U
 - Each diagonal block has edges directed to the blocks below in the same column (L-part), and the blocks on the right in the same row (U-part)
 - Each pair of blocks L(r,k) and U(k,c) have edges directed to block (r,c) for Schur complement update



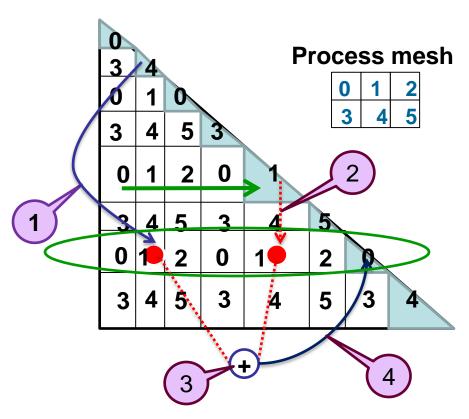
- ➤ Elimination proceeds from source to sink
- ➤ Over the iteration space

for k = 1 : N,
dags and submatrices become smaller

Triangular solution



$$x_i = \frac{b_i - \sum_{j=1}^{i-1} L_{ij} \cdot x_j}{L_{ii}}$$



- Higher level of dependency
- Lower arithmetic intensity (flops per byte of DRAM access or communication)

Examples



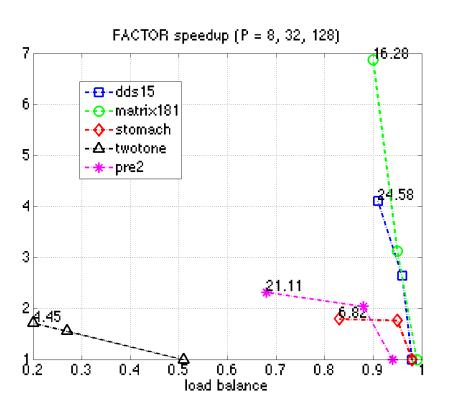
Name	Codes	N	A / N	Fill-ratio
dds15	Acclerator (Omega3P)	834,575	16	40.2
matrix181	Fusion (M3D-C1)	589,698	161	9.3
stomach	3D finite diff.	213,360	14	45.5
twotone	Nonlinear anal. circuit	120,750	10	9.3
pre2	Circuit in Freqdomain	659,033	9	18.8

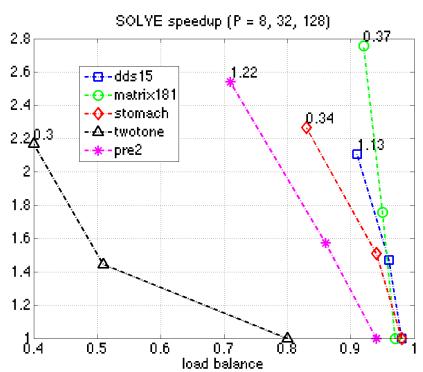
• Sparsity-preserving ordering: MMD applied to structure of A'+A

Load imbalance



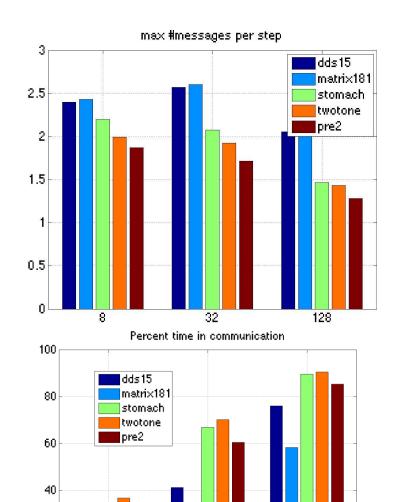
LB = avg-flops / max-flops

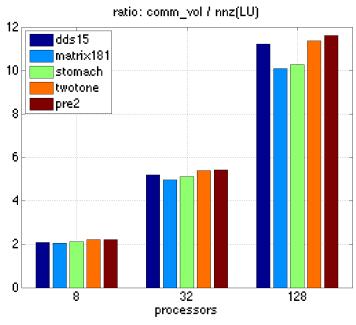




Communication



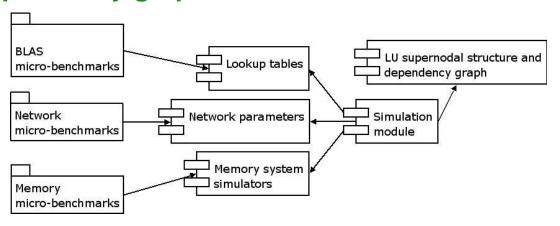


processors 

Current and future work



- LUsim simulation-based performance model [P. Cicotti et al.]
 - Micro-benchmarks to calibrate memory access time, BLAS speed, and network speed
 - Memory system simulator for each processor
 - Block dependency graph



- Better partition to improve load balance
- Better scheduling to reduce processor idle time